Journal of Cleaner Production 184 (2018) 1060–1071

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Does industrial green transformation successfully facilitate a decrease in carbon intensity in China? An environmental regulation perspective

Jian Hou [a,*], Thompson S.H. Teo [b,c], Fuli Zhou [d], Ming K. Lim [e,f], Heng Chen [a]

[a] School of Economics and Management, Harbin Engineering University, Harbin, China
[b] School of Business, National University of Singapore, Singapore
[c] School of Computing, National University of Singapore, Singapore
[d] School of Management, Chongqing University of Technology, Chongqing, China
[e] School of Mechanical Engineering, Chongqing University, China
[f] Centre of Supply Chain Improvement, The University of Coventry, United Kingdom

ARTICLE INFO

Article history:
Received 6 November 2017
Received in revised form
26 February 2018
Accepted 28 February 2018
Available online 3 March 2018

Keywords:
Industrial green transformation
Carbon intensity
Environmental regulation
Dynamic threshold model
China

ABSTRACT

Global climate change caused by carbon emissions poses a severe challenge to human economic and social development. The Chinese government has committed to a series of emission reduction initiatives to achieve carbon intensity targets by actively promoting the green transformation of the industrial sector—the main source of energy consumption and environmental pollution. This transformation has been ongoing for more than five years, and the effects, problems and experiences are worth discussing. Therefore, using province-level panel data for China's industry from 2010 to 2015, we systematically analyze the regional structure and developmental trend of industrial green transformation and empirically investigate its dynamic threshold effects on carbon intensity under different degrees of environmental regulation. The results show that China's industry has gradually undergone a green transformation, which has significantly reduced pollution emissions. However, the process has a large developmental scope due to regional heterogeneity and fluctuation characteristics. Interestingly, the impact of the industrial green transformation on carbon intensity is limited by the "critical mass" of environmental regulations. Paradoxically, weak environmental regulation significantly facilitates a decrease in carbon intensity through industrial green transformation. Once environmental regulation surpasses a critical level, the role of this transformation in CO_2 reduction is weakened, resulting in a failure to decrease carbon intensity. We provide insights into the driving factors that reduce carbon intensity and improve our understanding of the driving forces, paths and policy designs needed to successfully reach carbon intensity targets.

© 2018 Elsevier Ltd. All rights reserved.

1. Introduction

Carbon dioxide (CO_2) emissions, as one of the main contributors to environmental pollution, pose a severe challenge to the global ecosystem and socio-economic development. Reducing CO_2 emissions and realizing a low-carbon economy have become key measures used by all countries to address environmental challenges (Wang et al., 2012; Xu and Lin, 2016). As one of the world's most fossil fuel-dependent and carbon-intensive economies, China has surpassed the United States to become the world's largest emitter of CO_2 (International Energy Agency, 2009). The problem of haze pollution, which shrouded “the Gray Great Wall” and stretched for thousands of kilometers, is particularly severe in China (Hou et al., 2017). Total CO_2 emissions in China are affected by long-term sustained economic growth and industrialization and are likely to continue increasing. Because of the global push to reduce carbon emissions and considerable pressure from domestic support resources and environmental carrying capacity, the reduction of China's CO_2 emissions has become a focus of the international community. In December 2009, the Chinese government pledged that by 2020, carbon intensity would be reduced by 40%–45% compared to 2005 levels and would be incorporated as a binding indicator into the long-term planning of China's national economic

* Corresponding author.
E-mail addresses: houjian1128@163.com (J. Hou), bizteosh@nus.edu.sg (T.S.H. Teo), deepbreath329@outlook.com (F. Zhou), ac2912@coventry.ac.uk (M.K. Lim), chenh@hrbeu.edu.cn (H. Chen).

https://doi.org/10.1016/j.jclepro.2018.02.311
0959-6526/© 2018 Elsevier Ltd. All rights reserved.

and social development. In 2014, China and the USA issued the U.S.–China Joint Announcement on Climate Change in which China promised to reach peak CO_2 emissions near 2030. On 30 June 2015, China promulgated the Enhanced Actions on Climate Change, which indicates that by 2030, carbon intensity will be reduced by 60–65% compared to 2005 levels.

While the realization of these targets depends on the substantive transformation of the structure of regional economic growth, it depends even more on specific actions related to energy conservation and emission reduction in the industrial sector (Lü et al., 2015). China's economy is still in an industry-led developmental stage, with China's industrial GDP growing at an average annual rate of 11.5%. However, the basis of this extensive industrial growth is high energy consumption and high industrial emissions; it consumes 67.9% of the country's energy and emits 83.1% of the country's CO_2. Industry has become the main source of energy consumption and environmental pollution in China (Suh, 2016). In view of the significant role of industry in China's economic growth, energy consumption and carbon emissions, China's industrial sector must take the lead in realizing green transformation in the context of addressing emission targets. This leadership would have a positive demonstration effect on promoting the development of China's green economy and would also profoundly affect the push to decrease carbon emissions around the world.

In essence, industrial green transformation is a win-win situation for realizing intensive industrial growth and carbon emission reduction and for improving the contribution of green total-factor-productivity (TFP) to industrial economic growth under certain restrictions regarding energy and the environment. Reasonable environmental regulations that promote the continuous improvement of industrial green TFP will inevitably lead to the path of industrial transformation (Lü et al., 2015). Furthermore, behavior that affects carbon emissions is an externality in the process of production and consumption and requires supplementary restrictions in the form of environmental regulation. Therefore, industrial green development depends heavily on a series of environmental regulations. However, Schou (2002) argues that environmental regulations are unnecessary and that pollution will automatically decrease as natural resources continue to be consumed. Particularly since Sinn (2008) initiated the “Green Paradox” theory, scholars have increasingly raised doubts about the necessity and effectiveness of environmental regulation. Meanwhile, due to the regional heterogeneity of environmental regulation in China, the influence of driving factors on CO_2 emissions is uncertain. Thus, considering the different degrees of environmental regulations in China, what are the driving mechanisms of and differences in industrial green transformation as they relate to carbon intensity? Does industrial green transformation successfully facilitate a decrease in carbon intensity? How do we achieve CO_2 emissions-reduction targets for a green economy in the region? Due to the global low-carbon push, it is of theoretical value and practical significance to investigate the process of industrial green transformation and explore the driving forces, realized paths and policy designs for decreasing carbon intensity.

In this paper, we endeavor to provide a better understanding of the linkages between industrial green transformation, environmental regulation and carbon intensity by taking into account the perspective of “threshold effect”. First, we construct an index that can be used to evaluate the industrial green transformation in 30 provinces in China. This index captures the contribution of green TFP, including certain energy and environmental restrictions on industrial growth, by combining the slack-based measure and the Malmquist-Luenberger productivity index (SBM-ML). Second, we examine industrial green transformation and carbon intensity in various regions in China. We assume that a nonlinear relationship exists between industrial green transformation and carbon intensity. In doing so, we shed light on how different levels of regulation affect the relationship between industrial green transformation and carbon intensity, and whether thresholds or turning points exist in the relationship. The results provide a reference for regional policy-making with respect to the establishment of optimal industrial environmental regulation.

2. Literature review

Several studies have examined the characteristics and determinants of CO_2 emissions at industrial and regional levels through quantitative analysis, such as index decomposition analysis (Wang et al., 2016), structural decomposition analysis (SDA) (Lin and Xie, 2016), multi-objective optimization (Xu et al., 2015), and nonparametric additive regression models (Xu and Lin, 2017). The factors considered in these analyses are usually limited to energy intensity, technological change, industrial structure, etc. (Zhao et al., 2016). Furthermore, countermeasures and suggestions for promoting low-carbon production processes in industrial enterprises are often discussed. However, the existing literature has not conducted a direct study on the impact of industrial green transformation on carbon intensity, particularly in China. By considering green activities and CO_2 emissions as the main components of the industrial green transformation, we can still draw important references from relevant studies on the effect of industrial green transformation on carbon intensity.

According to scientific reports, CO_2 emissions are predominantly caused by industrial production and the combustion of fossil fuels (Intergovernmental Panel on Climate Change (IPCC), 2007). Industry is one of the most important energy-consuming sectors, resulting in a carbon intensity approximately 2.5–5 times that of tertiary industry. Therefore, the industrial green efforts in a specific region have a profound impact on carbon emissions (Suh, 2016). Diakoulaki and Mandaraka (2007) studied changes in CO_2 emissions in EU countries and found that most countries have made great efforts to reduce emissions, but the contribution to overall emission reduction is relatively small. Studying energy consumption and the efficiency of Japan's manufacturing industry, Sueyoshi and Goto (2014) also found that improving energy efficiency contributes to mitigating the energy intensity and CO_2 emissions of the manufacturing industry.

More researchers have begun to concentrate on China, and particularly its industries, since it has become the largest CO_2 emitter in the world. Regarding output, Zhao et al. (2010) analyzed the main factors responsible for industrial CO_2 emissions in Shanghai from 1996 to 2007 and found that reducing industrial output could decrease carbon emissions. Lin and Tan (2017) believe that the industrial scale is the main factor increasing CO_2 emissions. However, Chen et al. (2010) and Zhao et al. (2016) suggest that investment is the dominant factor increasing China's CO_2 emissions and that enhancing capital productivity and green investment would effectively mitigate CO_2 emissions. In addition, Zhang et al. (2017) indicated that investment intensity is the primary driver for the increase in China's industrial CO_2 emission intensity, while some uncertainty exists regarding the realization of the 2030 emission-peak target, and extra effort is needed to improve efficiency and structural adjustments. For energy-related activities, Lin and Liu (2016) investigated the transfer of CO_2 emissions between different industrial sectors. The regression estimation results indicate that energy consumption is the main factor in CO_2 emissions and that energy-saving technologies could significantly reduce energy intensity and CO_2 emissions. With the same method, Lin and Xie (2016) indicate that expanding the production scale led to increased CO_2 emissions, while a reduction in energy intensity

helped to reduce CO_2 emissions in China's food manufacturing industry. Therefore, decreasing economic activity and energy intensity can effectively help China achieve its 2020 and 2030 emissions targets (Wang et al., 2016). However, Lin and Tan (2017) also found that energy intensity is negatively related to emissions; therefore, reducing energy intensity is not conducive to achieving emission-reduction targets. Furthermore, energy efficiency improvements have been considered important for counteracting the expansion of carbon emissions. Thus, many previous studies have researched the energy efficiency of the industrial sector at the sector (e.g., Chang et al., 2013; Li and Shi, 2014) and provincial levels (e.g., Wang and Wei, 2014; Xiaoli et al., 2014). Improving energy efficiency helps reduce CO_2 emissions (Xu and Lin, 2016).

Therefore, because China's industry is responsible for considerable carbon emissions, policies such as the closure or phasing-out of industrial companies with backward production capacity will help to reduce energy consumption and emissions of environmental pollutants. (Zhu and Ruth, 2015) indicated that closer supervision and stronger regulation of CO_2 emissions is conducive for mitigating energy consumption and CO_2 emissions. The variation characteristics of the cumulative CO_2 emissions for each cycle during this period are well aligned with the stage characteristics of energy regulations, indicating that energy regulations play a consistent role in regulating such emissions (Wang et al., 2017). Clearly, environmental regulation plays an indispensable role in industrial sustainability and CO_2 emissions. However, scholars mainly focus on its linearity and ignore the threshold effect caused by different degrees of environmental regulation, particularly in China because of serious regional heterogeneity. The traditional view holds that environmental regulation increases the cost burden of enterprises, imposes new constraints on production performance, and causes the production, management and sale of enterprises to be more difficult, none of which are conducive to industrial green development (Cheng et al., 2017). In contrast, the Porter hypothesis (Porter, 1991) argues that regulation promotes innovation aimed at lowering the cost of compliance, which would in turn increase resource efficiency and product value, offset compliance costs and enhance firms' productivity. Many scholars have tested the Porter hypothesis (Cheng et al., 2017). However, due to regional heterogeneity, the degree of environmental regulation differs greatly. Usually, when environmental regulation intensity is weak, enterprises pay pollution costs to address environmental regulation. With the constant strengthening of environmental regulations, enterprises must transform, upgrade and update their equipment and technology to compensate for environmental compliance costs. Therefore, a threshold exists for the effects of environmental regulation (Wang et al., 2016; Xie et al., 2017).

Based on the previous research works summarized above, this study fills in the research gaps as follows. First, existing studies on industrial green transformation and carbon intensity are relatively sparse and are usually limited to examining energy intensity, technological change, industrial structure, etc. (Zhao et al., 2016). Further, past studies tend to focus on national, regional and industrial sector levels independently (Shi et al., 2017; Zhang et al., 2017; Zhao et al., 2016). We fill this gap by utilizing an extensive panel dataset encompassing 30 provinces in China, thereby including both the regional and industrial levels.

Second, most studies analyze the mechanism of CO_2 emissions for China's industry and describe the relationships between the variables using traditional econometric models that are based on economic theory. However, economic theory do not usually provide a rigorous description of the dynamic links among variables (Xu and Lin, 2016). Furthermore, because of continuity, inertia and the endogeneity of variables in the process from industrial green transformation to carbon intensity reduction, the traditional static method may not be sufficiently robust (Hou et al., 2017). In contrast, we used dynamic panel estimation method that takes into account the endogeneity and dynamic changes of the model, leading to more robust results.

Third, research on the current process of industrial green transformation is not definitive, particularly regarding quantitative index analyses. Moreover, although some of the literature reviews industrial sustainability and carbon intensity, few studies have considered industrial green transformation as a driving force or analyzed whether the industrial green transformation successfully facilitates a decrease in carbon intensity. In contrast, we investigate the process of industrial green transformation and explore the driving forces, realizing paths and policy designs for decreasing carbon intensity.

Fourth, a large number of nonlinear relationships embodied in economic variables have been largely ignored in past research (Anderson et al., 2015). Environmental regulation can nonlinearly affect green TFP and carbon emissions under significant regional heterogeneity and ignoring this nonlinear threshold of environmental regulation will lead to biased estimation results (Hou et al., 2017; Xie et al., 2017). Consequently, we took nonlinearity into account in our analysis. Our results shed light on how different levels of regulations affect the mechanism between industrial green transformation and carbon intensity, and whether thresholds or turning points exist in the relationship. We also improved on the threshold regression model to include the grouping test method. We used the dynamic panel estimation method to explore the effect coefficients and the difference between different threshold intervals. We also introduced threshold factors for the temporal and spatial heterogeneity of environmental regulation into the complex mechanism that links the industrial green transformation and carbon intensity to test whether the industrial green transformation successfully facilitates a decrease in carbon intensity in China.

Overall, this paper provides insights into the driving factors that reduce carbon intensity, and improve our understanding of the driving forces, paths and policy designs needed to successfully reach carbon intensity targets.

3. Measuring the industrial green transformation

3.1. Methodology

Industrial green transformation should not only reflect a transformation in the modes of industrial growth but also control for an increase in environmental pollution and ultimately realize low-carbon industrial development that incorporates green processes and environmental protections (Yang et al., 2013). Therefore, this paper considers the contribution rate of industrial green TFP, including energy and environment restrictions, to industrial economic growth as the measure of industrial green transformation (IGT) (Bin et al., 2013).

We assume that the industrial C-D production function is:

$$Y_{it} = I_{it} K_{it}^{\alpha} L_{it}^{\beta} E_{it}^{\gamma} \tag{1}$$

where Y_{it}, I_{it}, K_{it}, L_{it} and E_{it} represent the industrial production, green TFP, capital stock, labor stock and the energy consumption, respectively, of province i for year t. Log the two sides of the function and calculate the differential for t:

$$g_{Yit} = g_{Iit} + \alpha g_{Kit} + \beta g_{Lit} + \gamma g_{Eit} \tag{2}$$

Or,

$$\frac{g_{Iit}}{g_{Yit}} + \frac{\alpha g_{Kit} + \beta g_{Lit} + \gamma g_{Eit}}{g_{Yit}} = 1 \tag{3}$$

Thus, we can obtain the contribution rate of industrial green TFP to industrial output growth (*IGTit*):

$$IGT_{it} = \frac{(I_{it} - I_{it-1})/I_{it-1}}{(Y_{it} - Y_{it-1})/Y_{it-1}} = \left(1 + \frac{\alpha g_{Kit}}{g_{Iit}} + \frac{\beta g_{Lit}}{g_{Iit}} + \frac{\gamma g_{Eit}}{g_{Iit}}\right)^{-1} \tag{4}$$

① When $g_{Iit} > 0$, $\alpha g_{Kit} + \beta g_{Lit} + \gamma g_{Eit} > 0$, if $g_{Ait} > \alpha g_{Kit} + \beta g_{Lit} + \gamma g_{Eit}$, then:

$$0 < \frac{\alpha g_{Kit} + \beta g_{Lit} + \gamma g_{Eit}}{g_{Iit}} < 1 \Rightarrow 0.5 < IGT_{it} < 1 \tag{5}$$

where the growth rate of industrial green TFP is greater than the capital, labor and energy inputs, indicating that industrial growth has gradually realized the green transformation.

② By contrast, if $g_{Iit} < \alpha g_{Kit} + \beta g_{Lit} + \gamma g_{Eit}$, then:

$$\frac{\alpha g_{Kit} + \beta g_{Lit} + \gamma g_{Eit}}{g_{Iit}} > 1 \Rightarrow 0 < IGT_{it} < 0.5 \tag{6}$$

where the growth rate of industrial green TFP is less than the capital, labor and energy inputs, showing that industrial growth tends to be extensive, and the industrial green transformation has not yet been realized.

③ If $g_{Iit} \leq 0$, then $IGT_{it} \leq 0$, indicating that green TFP tends to decline or remain unchanged, and the industry has not yet begun the process of green transformation (Bin et al., 2013).

For the index of industrial green TFP at the province level (2010–2015), desirable output is measured by the total industrial output value and undesirable output is measured by the amount of discharged pollutants (industrial wastewater, industrial waste gas, and industrial solid waste), which are industry's main pollution sources. In addition, three inputs are included that correspond to capital, labor and energy. The labor force is measured by the number of employed workers. For green development based on energy efficiency (Hou et al., 2017), we adopt the indicators of final energy consumption to measure industrial energy input (The data are converted to million tons of standard coal by the equivalent coefficient of standard coal, which is derived from the China Energy Statistics Yearbook). Calculating capital stock is a complex process. Due to a large deviation in the results because of different depreciation rates and because the initial capital stock is computed by the perpetual inventory method, we consider the net value of the investment in fixed assets as a proxy (Xie et al., 2017). This paper investigates the effects of a series of emission-reduction measures and reforms that have occurred since the Chinese government made its commitment in 2009. Given the continuity, inertia and hysteretic nature of the process from industrial green transformation to carbon intensity reduction, we calculate the growth rate of each period, using 2009 as the initial stage, and define the sample range as 2010 to 2015 due to the availability of statistical data.

3.2. Analysis of industrial green transformation

Overall, the average value of China's industrial green transformation is 0.3121 (Fig. 1), which means that China's industrial growth is intensifying. Given that the measurement of industrial green TFP controls for environmental pollution, industrial green transformation is gradually beginning to take effect under the implementation of a series of environmental measures. However, due to regional differences such as industrial structure, capital investments, human resources, industrialization level, and the economic foundation, the process of industrial green transformation still shows fluctuating characteristics and has failed to form a unified trend. A large scope remains for further development to fully realize the green transformation of China's industrial sector. Specifically, regions with high levels of transformation include Tianjin, Neimenggu, Jiangsu, Zhejiang, Shandong, Hubei, Xinjiang and Hainan. Interestingly, these provinces are not all concentrated in the eastern developed areas, which is inconsistent with the traditional view. The central and western regions of Neimenggu, Xinjiang and Hainan have optimized the industrial structure; considering the geographical features and natural resources of these areas, their economic structures have been vigorously adjusted in recent years, relatively reducing energy consumption and environmental pollution by focusing on ecological protection and development. These regions are highly dependent on significant structural optimization. Considerable progress has not been made in R&D or energy-saving innovations due to the weak economic foundation, which cannot fully support green transformation in the long run. Tianjin, Jiangsu, Zhejiang and other eastern coastal areas rely on a developed economy and industrialization. However, they have advanced technologies in clean production and pollution control and high awareness of green innovation and environmental protection. Thus, these areas have initially realized a transformation of economic development, and this green growth can be further upgraded by strengthening environmental technological innovation and green transformation. For Beijing, Liaoning, Shanghai, Guangdong, Chongqing and other provinces with low transformation levels, although they have great advantages in energy conservation, emission reduction and green technological innovation supported by a considerable economic foundation and industrialization, they are also responsible for the country's most intensive industrial pollution and energy consumption. For example, the Blue Book of World Cities: Annual Report on World Cities (2014) issued by Shanghai Academy of Social Sciences noted that ecological problems have become the largest challenge to upgrading the city of Beijing, and its ecosystem score is the last but one among 40 global cities (Shanghai Academy of Social Sciences, 2014). According to the Beijing Municipal Environmental Protection Bureau, the city consumes 6831 million tons of standard coal, and the pollution emission is roughly equivalent to an increase in the emissions of a medium-sized city on the basis of the city's total pollution emission in 2014. At present, Beijing's annual coal consumption is 2600 million tons, which makes it the largest coal-burning metropolis in the world. Because coal is the city's main source of energy, the city is responsible for 3569.2 billion cubic meters of industrial waste gas emissions. In particular, the annual mean in PM2.5 is 1.30 times higher than the national standard (Beijing Municipal Environmental Protection Bureau, 2014). Wastewater discharge is 150714 million tons, and solid waste production is up to 1036 million tons (National Bureau of Statistics of China, 2015). The emissions of waste gas, waste water and solid waste are all increasing. Moreover, the substantial demand factors for infrastructure development such as central heating, motor vehicles, road congestion, dense population and industrial and urban construction have caused serious pollution in local areas. The industrial green transformation of these areas is deeply affected by industrial overcapacity, and pollution emissions are considerable.

As the center and key hub of the national resource allocation, these areas are highly concentrated in population and economic activities. With the rapid development of the economy and urban construction, the negative effects of these activities on resources

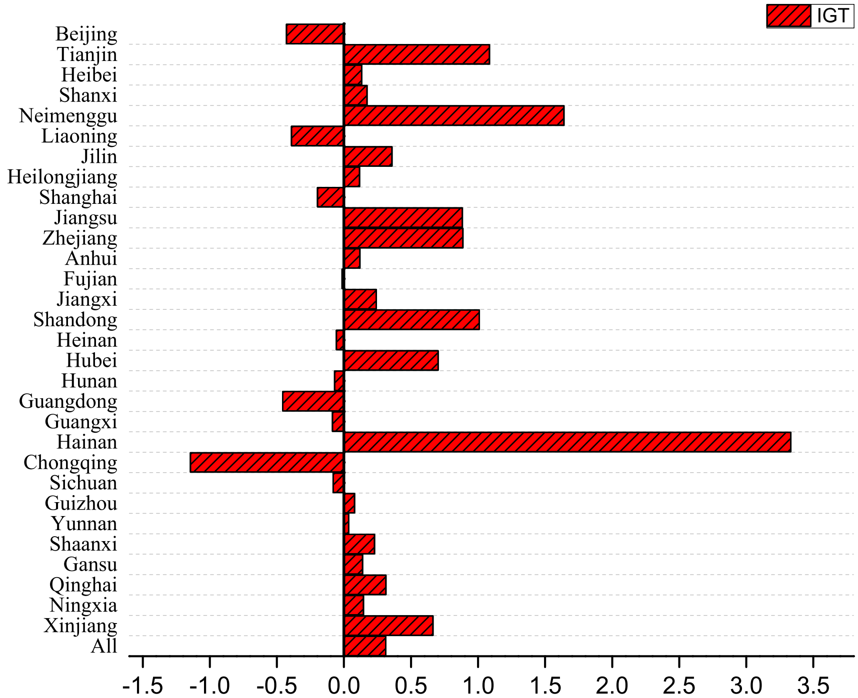

Fig. 1. Index of industrial green transformation in China (2010–2015). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

and the environment are obvious, which is more serious than the short-term effect of structural adjustment. The improvement of green transformation and structural optimization is phased and lagging. It needs long-term continuous development to compensate for the environmental transformation. Therefore, even though the government is constantly shifting traditional industries, adjusting the economic structure, and implementing green technology, because the population and economic intensity with its environmental pressures are increasing rapidly, the benefits of this transformation have not been fully realized in the short term.

We construct a spatial distribution map of industrial green transformation that illustrates the levels in 2010 and 2015 (Fig. 2). In 2010, after the government began to clearly propose emission-reduction targets, the industrial growth patterns of most provinces still tended to be extensive. At that time, the industrial sector had neither started nor achieved its green transformation ($IGT = 0$, $0 < IGT < 0.5$), suggesting that prior industrial expansion emitted a large amount of CO_2 and caused serious environmental pollution. With the continuous promotion of the green transformation, we can observe that the number of provinces with positive transformation are increasing and the growth tends to be intensive. By 2015, industrial growth in the vast majority of provinces was actively transforming to a green ecology, and environmental pollution was strictly controlled. Among these provinces, Hainan, Tianjin and Shandong have taken the lead in realizing a green transformation. However, we find that the dependence of industrial growth on resources, capital, labor and energy inputs in some provinces—such as Beijing, Liaoning and Chongqing—has not

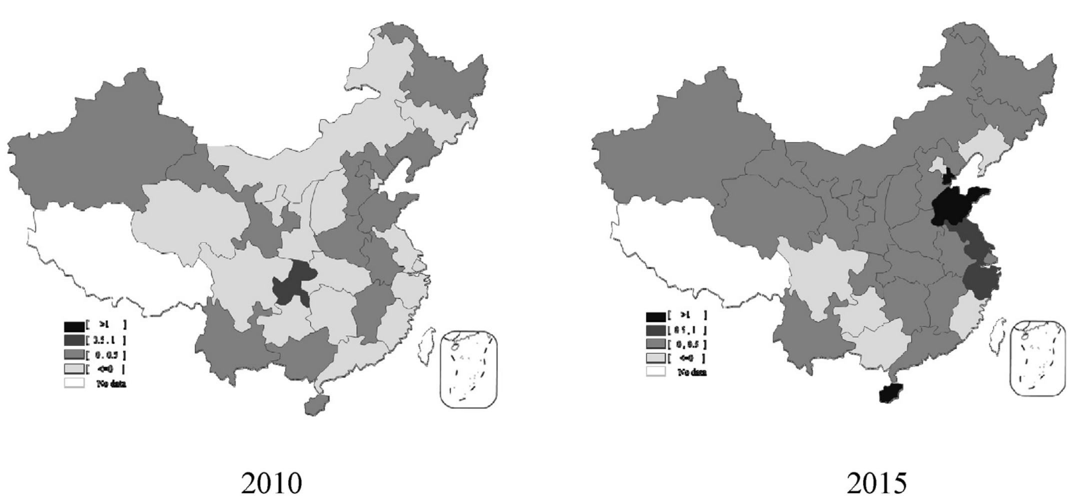

Fig. 2. Spatial distribution of the industrial green transformation in China (2010 and 2015).

weakened. Instead, some signs indicate that this dependence has strengthened. Therefore, attention should be paid to areas where the green transformation effect is not sufficiently effective.

4. Empirical model and variables

4.1. Specifications of the dynamic threshold model

Based on the theoretical framework of the mechanism of industrial green transformation, we note that China's regional heterogeneity is substantial. Ignoring this key factor of China's regional environmental regulation will cause a biased estimation. In other words, when an economic parameter reaches a certain value, it causes another economic parameter to suddenly affect other forms of development. The critical value at the root of this phenomenon is termed the threshold value, which is also known as the problem of nonlinear “structural change”. From a methodological perspective, samples must be tested on both sides of the critical value of environmental regulation in China. Hansen (1999) first proposed the idea of the panel threshold regression model, which uses a threshold variable to determine the points of structural change and then forms observation values to estimate the true threshold value, thereby processing the structural changes of nonlinear problems more objectively and accurately (Hansen, 1999). Hansen's nonlinear threshold panel regression is very effective for capturing nonlinear threshold characteristics caused by structural mutation in an economic system due to the automatic identification of sample data. Moreover, this method also has the positive characteristics of the general panel data model. However, this threshold method is applicable only to the non-dynamic panel model. It cannot reflect dynamic change or the lag effect of a sample object, and it also ignores the processing of endogenous variables. Thus, we first estimate the threshold value using the Hansen method (More detail can be found in Hansen (1999)) and further use the “first-order difference GMM” (Arellano and Bond, 1991) to estimate the parameters between different threshold regimes. In this manner, we can control the lag effect, endophytism and dynamic factors based on the dynamic panel estimation method. We find that the dependent variable of the two-order lags is significant, and the fitting degree is the best. Therefore, we choose the first-order and two-order lags to control for the continuity and inertia of the process of reducing carbon intensity. Using a single-threshold model as an example, the specification is as follows:

$$\begin{aligned} CO_{2_{it}} &= \theta + \alpha_1 CO_{2it-1} + \alpha_2 CO_{2it-2} + \alpha_3 ENE_{it} + \alpha_4 URB_{it} + \alpha_5 INO_{it} + \alpha_6 STR_{it} + \alpha_7 FDI_{it} \\ &+ \alpha_8 OPE_{it} + \beta_1 IGT_{it} I(REG_{it} \le \gamma) + \beta_2 IGT_{it} I(REG_{it} > \gamma) + \mu_i + \nu_t + \varepsilon_{it} \end{aligned} \tag{7}$$

where the subscripts i and t denote province and year, respectively. CO_2 is carbon intensity, IGT is industrial green transformation, and REG is environmental regulation. $I(\cdot)$ is the indicator function, and γ is the threshold value. The observations are divided into two regimes depending on whether the threshold variable REG_{it} is less than or greater than the threshold value γ. The regimes are distinguished by differing regression slopes, β1 and β2. A series of control variables are also included: energy intensity (ENE), urbanization (URB), innovation effect (INO), industrial structure (STR), foreign direct investment (FDI) and trade openness (OPE). μ_i is the specific effect of the individual, υ_t is the specific effect of time, and ε_{it} is a random disturbance.

4.2. Variables and data sources

This paper estimates the relationship between industrial green transformation, environmental regulation and regional carbon intensity. The IGT index is the result of the above calculations. Environmental regulation varies greatly across China. To analyze the heterogeneous effects of environmental regulation on the relationship between IGT and CO_2, the common approach in the existing literature is to use pollution abatement and control expenditures as a proxy for environmental regulations (Hamamoto, 2006; Xie et al., 2017). Meanwhile, environmental investment is most widely used for environmental regulation in China. According to the National Bureau of Statistics of China, environmental investment includes urban environmental infrastructure facilities, environmental components for “three-simultaneity" new construction projects, and the treatment of industrial pollution sources, which involve pollution-fee subsidies, government subsidies and fees paid by enterprises. All these treatment activities have a significant influence on industrial green development. Because limited province-level data are available from the Chinese government, we use investment in the treatment of industrial pollution sources by industry as a proxy for environmental regulation (REG) (Hou et al., 2017). We use the ratio of regional carbon emissions (CE) to GDP as the regional carbon intensity (CO_2). Since China has no direct statistical data on carbon emissions, and fossil fuel combustion is the main source of CO_2 emissions, existing studies generally use energy consumption to estimate CO_2 emissions (Cheng et al., 2017; Dong et al., 2017; Wang et al., 2016; Zhao et al., 2016). Based on energy consumption (We includes 8 major fossil energy sources outlined in the China Energy Statistical Yearbook, including coal, coke, crude oil, gasoline, diesel fuel, fuel oil, natural gas and kerosene), this paper calculates total CO_2 emissions using the method provided by the IPCC, and the formula is as follows:

$$CE = \sum_{i=1}^{8} (CO_2)_i = \sum_{i=1}^{8} E_i \times NCV_i \times CEF_i \tag{8}$$

where CE represents carbon emissions; i denotes the fossil fuel category; E denotes fossil fuel consumption; NCV denotes the low calorific value, which is provided by the Chinese government; and CEF is the CO_2 emissions coefficient of fossil fuel from the IPCC (Table 1).

Six control variables of interest are included in our investigation. First, energy consumption is the primary factor behind regional emissions. We measure energy intensity (ENE) using the ratio of regional energy consumption to GDP. Second, we include an urbanization (URB) variable defined by the proportion of urban population. Third, the transformation and upgrading of China's industry is increasingly dependent on the innovation effect (INO). Through green innovation, the industry has advanced clean production and pollution-control technology, driving industrial green development. Fourth, a variable for industrial structure (STR) is included, which is defined as the proportion of GDP of secondary industry. Fifth, FDI increases the host country's emissions and leads

Table 1
The low calorific value and CO_2 emissions coefficients.

	Coal	Coke	Crude oil	Gasoline	Diesel	Fuel oil	Natural gas	Kerosene
NCV (KJ/kg·m3)	20908	28435	41816	43070	42652	41816	38931	43070
CEF (kgCO_2/TJ)	95333	107000	73300	70000	74100	77400	56100	71500

to the "pollution haven" effect. However, it also promotes industrial green production and reduces environmental pollution by introducing green technologies. Finally, regional carbon intensity cannot be separated from the global value chain system with trade openness (OPE) as the main supporter of an open economy. We use the ratio of total regional imports and exports to GDP as a proxy.

Table 2 summarizes the descriptive statistics of all variables. The province-level panel data for 2010–2015 is obtained from the database of the National Bureau of Statistics of China. The nominal variables are deflated into real ones by using the GDP deflator index and the fixed-asset investment price index for 2010.

5. Empirical results and discussions

5.1. Results of threshold effect tests

First, we examine whether a significant nonlinear relationship exists and further determine the number of thresholds. The F statistic and p-value are obtained using the bootstrapping method (Table 3). We find that a single threshold is significant at the 5% level and a double threshold is significant at the 10% level, while the triple threshold is not significant because the bootstrap p-value is 0.106. According to Hansen's threshold model, the relationship between industrial green transformation and carbon intensity has two thresholds in terms of environmental regulation.

Second, with environmental regulation as the threshold variable, the double threshold values are 11.764 and 11.867 for the driving effect of industrial green transformation. Moreover, both threshold estimate values are in the 95% confidence interval: 11.764 [9.284, 11.793] and 11.867 [10.882, 12.066]. The results are shown in Table 4.

Finally, the function chart of the threshold variable 'likelihood ratio' sequence, with the well-defined change in threshold value, shows the structure of the estimate and the confidence interval (Fig. 3). Specifically, we use the likelihood ratio $LR_n(\gamma)$ to construct the "non-rejection region", which indicates the valid confidence interval of γ. The "non-rejection region" at the confidence level of $1-\alpha$ is a series of γ values that belong to $LR_n(\gamma) \le c(\alpha)$. When $LR_n(\gamma) \le c(\alpha) = -2ln(1-\sqrt{1-\alpha})$ (α is the level of significance, and $c(\alpha) = 7.35$ at the 95% confidence level), we cannot reject the null hypothesis that the threshold estimate is equal to the true value ($H_0 : \gamma = \gamma_0$) (Hansen, 1999). This corresponds to the horizontal line in Fig. 3.

Table 2
Descriptive statistics of variables.

Variable	Mean	P50	S.D.	Min	Max
CO_2	27.668	22.411	17.861	5.482	90.253
REG	11.496	11.644	0.981	8.441	13.110
IGT	0.061	0.177	2.477	−15.492	8.813
ENE	0.941	0.803	0.449	0.360	2.179
URB	54.858	52.220	13.008	34.700	89.600
INO	9.607	9.782	1.472	6.219	12.430
STR	47.431	49.600	8.005	21.300	58.400
FDI	0.020	0.016	0.016	0.002	0.076
OPE	0.302	0.143	0.351	0.039	1.472

Table 3
Threshold significance test.

	Critical value				
	F-value	P-value	1%	5%	10%
Single threshold	2.179**	0.024	2.700	1.657	1.264
Double threshold	10.068*	0.071	49.919	14.800	6.042
Triple threshold	1.276	0.106	6.359	2.031	1.318

Note: The p-value and the critical value are obtained by using the "self-sampling method" (bootstrap) with 800 replications.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 4
Results of threshold estimators and confidence intervals.

Model	Threshold estimators	95% Confidence intervals
Single threshold	9.938	[9.284, 12.809]
Double threshold	11.867	[10.882, 12.066]
	11.764	[9.284, 11.793]
Triple threshold	9.938	[9.284, 13.106]

5.2. Estimation results of the dynamic threshold model

Once the significant thresholds were found, we divided the regulation stringency into different degrees: weakly regulated (REG≤11.764), moderately regulated (11.764 < REG≤11.867) and strongly regulated (REG>11.867). Then, we further use the dynamic estimation method of the first-order difference GMM to estimate the partition coefficient between different degrees.

Table 5 reports the estimates of the effects of industrial green transformation on carbon intensity under different degrees of environmental regulation. When the industry is weakly regulated (REG≤11.764), its green transformation has a significant negative impact on regional carbon intensity at the 1% level. The implementation of industrial green transformation can significantly reduce regional carbon emissions and effectively reduce regional carbon intensity. As environmental regulation is strengthened, the mechanism differs: when moderately regulated (11.764 < REG≤11.867), the negative impact on regional carbon intensity is not significant. However, when the threshold value is higher than 11.867 (strongly regulated), the effect coefficient changes from negative to positive, and it is significant at the 5% level. This result reflects the "critical mass" of environmental regulation in China. A weaker level of environmental regulation is conducive to reducing carbon intensity through the industrial green transformation. However, once a critical level is reached, namely, the level of regulation becomes stronger, the effect of emission reduction from the transformation is clearly weakened, which will not facilitate a decrease in carbon intensity.

For the other driving forces reducing regional carbon intensity, INO and FDI both have a significant negative impact on carbon intensity, showing that technological innovation and FDI can be used to promote industrial green production and reduce carbon emissions, which does not lead to a "pollution haven" effect. The effects of STR and OPE on carbon intensity are negative, but not significant. To some extent, there is no evidence that they played a role in promoting the growth of regional carbon intensity. ENE has a

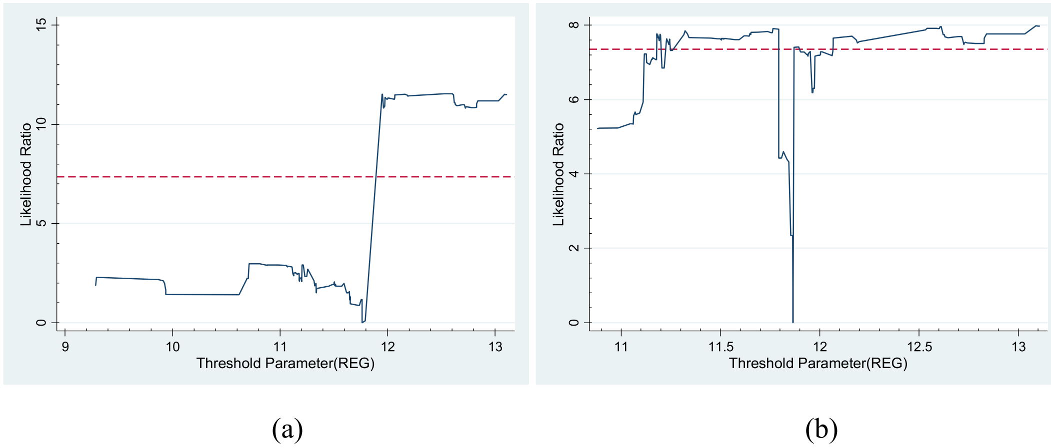

Fig. 3. The construction of confidence intervals. (a): The first threshold value. (b): The second threshold value.

Table 5
Results of dynamic threshold regression.

CO_2	Coef.	Std. Err.	z	P>|z|	95% Conf. Interval	
L1.	.922***	.168	5.48	0.000	.592	1.251
L2.	-.157***	.040	−3.90	0.000	-.235	-.078
ENE	9.075***	2.508	3.62	0.000	4.159	13.991
URB	.322	.226	1.42	0.155	-.121	.765
INO	−2.560***	.788	−3.25	0.001	−4.104	−1.016
STR	-.017	.074	−0.23	0.816	-.162	.128
FDI	−206.895***	65.893	−3.14	0.002	−336.044	−77.747
OPE	-.129	1.954	−0.07	0.947	−3.958	3.700
IGT(REG≤11.764)	-.135***	.0173	−7.79	0.000	-.168	-.101
IGT(11.764 < REG≤11.867)	-.139	.105	−1.33	0.185	-.345	.0664
IGT(REG>11.867)	.112**	.052	2.18	0.029	.012	.213
_cons	9.361	9.579	0.98	0.328	−9.414	28.136

Note: GMM-type: L(2/.). CO_2.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

significant positive impact on carbon intensity, which can aggravate regional pollution from carbon emissions. Therefore, the regions need to control total energy consumption in their areas to accelerate the upgrading of green production technologies, increase the utilization of clean energy, and gradually optimize the consumption structure that is dominated by coal. China's urbanization has also promoted an increase in carbon intensity, but it is not significant. From a practical viewpoint, we still need to focus on the contradictions among economic growth, energy consumption and environmental pollution caused by urbanization and avoid the aggravation of regional environmental contradictions.

5.3. Discussion

Generally, environmental regulation is necessary to decrease regional carbon intensity. However, unlike previous studies, we find that as the level of environmental regulation increases, the effect of industrial green transformation on carbon intensity is, interestingly, the opposite. The two natural attributes of environmental elements, “scarcity” and “externalities”, cause green TFP to differ from general technology, which causes the industrial green transformation and regional carbon intensity to become more sensitive to the intensity of environmental regulation. Blindly strengthening environmental regulation cannot reduce regional carbon intensity by improving green TFP and promoting the transformation of China's industrial growth mode. We believe that this relationship depends on the “extrusion effect” and the “compensation effect” that occur with different degrees of environmental regulation. In the case of China, for stronger degrees of regulation, the extrusion effect is greater than the compensation effect. More specifically, China's industrial growth mode continues to show the following characteristics: it relies mainly on a resource path that entails high investment, high energy consumption, and high emissions, and it is approaching the limit of its environmental carrying capacity. Based on this background, environmental regulation affects industrial enterprises, resulting in two kinds of behavior. One is to increase environmental production and technology investment to reduce pollution emissions, and the other is to purchase environmental TFPs. Both of these behaviors increase industrial costs. Thus, the forced mechanism is formed of industrial technology improvement and the optimization of resource structure.

When environmental regulation intensity is low, the tolerance level of industry to pollution treatment costs is higher, and the “compensation effect” is stronger, which allows industry to increase the input of production factors to obtain economic output to offset the increasing costs of regulation costs. In addition, it is helpful for improving the motivation of the industrial sector to update to more efficient production equipment, promote the integration of green technology and production, optimize green production and technical conditions and subsequently, reduce energy consumption and emission pollution, promote the emission-reduction effect of industrial green transformation, and facilitate the ability to reach carbon intensity targets.

However, when industry is strongly regulated, the inhibiting effect of environmental regulation on industrial emission reduction

dominates, particularly for the emission-intensive industrial structure in China. The "compensation effect" cannot effectively compensate for the "extrusion effect", thus reflecting the green paradox theory of environmental regulation. First, economic intuition indicates that given the large number of negative externalities of production activities, such as "energy", the higher the intensity of environmental regulation is, the higher the cost of pollution governance becomes. Thus, the "extrusion effect" is more likely to dominate. Furthermore, because of the negative externalities of energy factors, most industrial enterprises passively choose end-of-pipe treatments. When there is an increase in environmental regulation intensity and the marginal performance of end-of-pipe treatment diminishes, enterprises will absorb higher environmental costs. When industrial enterprises have limited funds, they are subject to the significant adjustment costs of environmental technology and will increase the input of production factors. These investments will be diverted to the original funds used for pollution control and green innovation to conduct technological innovation that cannot compensate for the costs related to regulation, which affects normal R&D activities, thereby reducing the efficiency of industrial green development. Therefore, the long-term cost of strong levels of regulation is too high, and the effect of the industrial green transformation is poor. The "extrusion effect" and green paradox are significant.

Second, environmental regulations cause environmental resources to emulate the characteristics of economic goods. When industrial enterprises consume environmental resources for production, they must pay certain expenses, causing the product price to increase. The condition of constant demand will inevitably lead to a reduction in profit margins, thus reducing the motivating force to engage in environmental activities. Notably, strong environmental regulation will exceed industrial capacity and hinder improvements in production efficiency, technological progress and green transformation. However, when environmental regulations are stricter, fossil energy prices are lower (Sinn, 2008). In the short term, rising demand for cheaper fossil fuels stimulates an increase in carbon emissions, resulting in the green paradox effect.

Moreover, if current environmental regulation is strengthened, a new constraint will be imposed on the production decisions of industry in China: strong environmental regulation absorbs a portion of the financial resources and represents a considerable proportion of management costs (Wanlley, 1994). Such regulation has an adverse effect on the management and sales of green production, and some investment projects with superior profitability and sustainability prospects may become inefficient, which is not conducive to decoupling regional CO_2 emissions from industry outcomes (The OECD (2002) defined decoupling as separating the link between economic production and environmental pollution).

In conclusion, if the intensity of industrial environmental regulation at this stage is further increased beyond the limits that industry can afford, it will not only fail to achieve the win-win situation between the economy and the environment described by the Potter hypothesis but also hinder the ability of most industrial enterprises, which have low levels of benefit and outdated technical equipment, to meet the environmental standards in a short period of time. As a result, these firms either escape from pollution reduction or pursue rent-seeking behavior, which subsequently motivates the industry to prefer sacrificing the environment to actively increasing investment in environmental protection.

Finally, the lag variables are significant at the 1% level, which indicates that the dynamic panel threshold model constructed in this paper is reasonable. The Sargan tests show prob > $\chi 2 = 0.6119$, which does not allow us to reject the null hypothesis that the instrumental variables are reasonable at the 10% level. Neither do the AR (1) and AR (2) tests (Table 6) reject the null hypothesis that there is no autocorrelation of $\{\varepsilon_{it}\}$; the model setting and the use of a first-order difference GMM are more reasonable.

Table 6
AR (1) and AR (2) test.

Order	z	Prob > z
AR (1)	−2.689	0.007
AR (2)	.0132	0.989

5.4. Robustness test

To ensure the credibility of the results, we further conduct a robustness test to verify the impact of industrial green transformation on carbon intensity. Considering this paper is a dynamic panel estimation, and the system-GMM method proposed by Blundell and Bond (1998) is also one of the most popular classical dynamic estimation methods, we use the system-GMM regression method to re-estimate the slope coefficient between thresholds. The system-GMM estimation combined with differential GMM and level GMM not only addresses endogenous problems well, but also effectively reflects the dynamic change characteristics.

From Table 7, we can see that compared with the results of dynamic threshold regression in Table 5, the model does not change significantly, especially within the different thresholds of environmental regulation. The overall estimation results are credible and robust. The model set is also technically sound. When the industry is weakly regulated (REG≤11.764), its green transformation has a significant negative impact on regional carbon intensity at the 1% level. As environmental regulation is strengthened, the mechanism differs: when moderately regulated (11.764 < REG≤11.867), the negative impact on regional carbon intensity is not significant, while when the threshold value is higher than 11.867 (strongly

Table 7
Results of the robustness test.

CO_2	Coef.	Std. Err.	z	P>|z|	95% Conf. Interval	
L1.	.965***	.013	73.01	0.000	.939	.990
ENE	1.037**	.467	2.22	0.027	.121	1.952
URB	-.012	.014	−0.86	0.388	-.039	.015
INO	-.212*	.108	−1.96	0.050	-.423	-.000
STR	.023*	.013	1.75	0.080	-.003	.049
FDI	−2.230	6.656	−0.33	0.738	−15.274	−10.816
OPE	1.562***	.484	3.22	0.001	.612	2.511
IGT(REG≤11.764)	-.060***	.020	−2.97	0.003	-.100	-.021
IGT(11.764 < REG≤11.867)	-.027	.027	−1.00	0.318	-.081	.026
IGT(REG>11.867)	.047*	.025	1.79	0.073	-.004	.098
_cons	-.113	1.415	−0.08	0.937	−2.886	2.660

regulated), the effect coefficient changes from negative to positive and is significant at the 10% level. Weak environmental regulation significantly facilitates a decrease in carbon intensity through industrial green transformation. Once environmental regulation surpasses a critical level, the role of this transformation in CO_2 reduction is weakened, resulting in a failure to decrease carbon intensity. Regarding control variables, INO and FDI both have a negative impact on carbon intensity, and ENE has a significant positive impact on carbon intensity. These results are all in line with the results in Table 5. Because the results of URB, STR and OPE in Table 5 are not significant, together with differences in local factors and limitations of the sample and method calculation, to some extent, there is no evidence that their impact on carbon intensity is a consistent conclusion (Cheng et al., 2013; Hou et al., 2017; Xie et al., 2017; Zhang et al., 2014).

6. Conclusions

Achieving carbon intensity targets by industrial green transformation is a project involving high levels of uncertainty and complexity. Combining the SBM model and the ML index and using an extended dynamic threshold model, this paper systematically analyzes China's industrial green transition, identifies the main driving forces of carbon intensity, explores the role of industrial green transformation in reducing carbon intensity from the perspective of environmental regulation, and finally, provides interesting insights into the implications for facilitating carbon intensity targets.

Overall, China's industrial growth is becoming intensive, and its green transformation has gradually taken effect under the implementation of a series of environmental measures. However, the process of industrial green transformation is still showing fluctuating characteristics that vary regionally and fail to form a unified trend. Clearly, attention should be paid to the transformation effect in Beijing, Liaoning and Chongqing because it is insufficient for reducing carbon emissions.

The regional heterogeneity in the process of China's industrial green transformation is significant, and the provinces with superior transformation performance are not all concentrated in the eastern developed areas. Most of the eastern areas should focus on not only the advanced conditions of environmental treatment but also on optimizing the industrial and economic structure as soon as possible. While the majority of the central and western areas are mainly dependent on significant structural optimization, green R&D and innovation have not made great progress and cannot fully support green transformation in the long run.

The effect of the industrial green transformation on carbon intensity is significantly limited by the “critical mass” of environmental regulation. Weak degrees of regulation will successfully facilitate a decrease in carbon intensity through industrial green transformation. Once environmental regulation reaches a critical level, namely, stronger degrees of regulation, its ability to reduce CO_2 emissions will clearly weaken, and it will not succeed in decreasing carbon intensity.

Regarding the other driving forces that facilitate our ability to reach carbon intensity targets, both INO and FDI can be used to promote industrial green production and reduce carbon intensity, while ENE does not help to reduce regional carbon intensity. To some extent, there is no evidence that STR and OPE play a role in promoting an increase in regional carbon intensity. Finally, regions should also avoid the aggravation of environmental contradictions caused by China's urbanization.

Based on the findings above, we recommend the following policy pathways to reach China's carbon intensity targets.

First, China faces global low-carbon competition and a grim situation regarding the availability of supporting resources and the environmental carrying capacity. However, because its industry is the main source of economic growth, energy consumption and environmental pollution, achieving green transformation will have a profound impact on the world economy and low-carbon development. At present, industrial growth in most of China's regions is actively transforming to a green ecology. Because of this apparent operability, industry can take the lead in achieving a green transformation to improve the contribution of green TFP to industrial growth, despite energy and environmental restrictions, and achieve a win-win outcome that includes both intensive industrial growth and CO_2 emission reduction. This outcome would also have a positive demonstration effect on promoting the development of China's green economy. Second, regions should fully consider regional gaps in the process of the industrial green transformation and implement the institutional designs of a green system according to the regional economic geographical heterogeneity. The first regions to complete the industrial green transformation mainly rely on optimizing industrial structure, but they lack significant progress in R&D in energy conservation and emission reduction. Because of a weak industrial foundation and a lack of technical funds, knowledge accumulation and talent resources to fully support the green transformation in the long run, certain areas need to focus more on green innovation, increasing investment in green technology R&D, engaging in external cooperation, and internalizing and absorbing external green technology. Then, these areas should accelerate the popularization and application of energy-saving and emission-reduction technology and promote the integration of green technology and production. Meanwhile, the government should develop more preferential tax and financial policies for regional industries that cooperate and develop more green technology to optimize industrial green technical conditions, which in turn increases the basis of industrial green R&D, reduces innovation costs and risks, and supports sustainable development for the industrial green transformation. However, regions where the process of industrial green transformation is slow or has not yet been achieved should not only focus on improving environmental treatment conditions but also emphasize the optimization of the economic and industrial structure as soon as possible. These areas should consider that optimizing the industry structure is the core transformation process and should gradually shift away from a consumption structure that is dominated by coal and transform the current growth mode that requires high investment, high energy consumption, and high-pollution by reducing energy intensity with a circular economy. In addition, these areas should cultivate and develop emerging industries—such as new energy, new materials, and high-tech and high-end service industries—to realize a green ecological chain for industry. Third, considering the heterogeneous threshold effect of environmental regulation, environmental regulation must be rationally designed to successfully facilitate the ability to reach targets in different regions. Additionally, it is necessary to remain vigilant regarding the adverse effects of strong degrees of regulation. As the strongly regulated period shows, the extrusion effect is greater than the compensation effect, and the significant differences exist in different regions in China, in particular, provinces with stronger environmental regulation should maintain stable regulation levels to avoid blindly increasing the intensity of industrial environmental regulation, thus exacerbating the restrictive role of the “compensation effect”. Weakly regulated areas can make full use of the “compensation effect” of innovation to promote industrial green transformation and effectively realize a win-win situation in which regional emission goals are achieved and ecological development thrives. Finally, to improve our ability to meet carbon intensity targets, multiple driving factors should be addressed regionally. Local governments

should develop regional policies to promote FDI and trade openness with efficient, clean technology based on their own economic conditions. In addition, local governments should pay attention to their green technology content and digestion-absorption ability through FDI and foreign trade and actively introduce advanced green technology and production processes. Moreover, in China, the scale of cities has expanded rapidly in a short time, which means that the corresponding management system, environmental structure and governance system should be improved and perfected. Thus, the burden on resources and the environment will be reduced, and areas can avoid the contradiction that occurs among economic growth, energy consumption and environmental pollution due to urbanization.

Acknowledgments

This work was supported by the PhD Student Research and Innovation Fund of the Fundamental Research Funds for the Central Universities (HEUGIP201718) and the China Scholarship Council (CSC).

Appendix A

A.1. The SBM model and the Malmquist-Luenberger index

First, according to the environmental technology function (Färe et al., 2007), the matrix $X=(x_{ij})\in R^{+}_{nm}$ is defined as the input vector, $Y^g=(y^g_{ij})\in R^{+}_{um}$ is the desirable output vector, and $Y^b=(y^b_{ij})\in R^{+}_{vm}$ is the undesirable output vector. Assume that the production-possibility frontier satisfies the closed-convex set and includes both the weak disposability and strong manageability of desirable outputs and inputs; then, environmental technology can be expressed as follows:

$$P(x)=\left\{\left(x,y^g,y^b\right)\middle| x\geq X\lambda, y^g\leq Y^g\lambda, y^b=Y^b\lambda, \sum_{i=1}^{m}\lambda=1,\lambda\geq 0\right\} \tag{A.1}$$

where λ is the weight variable; $\sum_{i=1}^{m}\lambda=1$ indicates the variable returns to scale (VRS); and $\lambda\geq 0$ removes the constraint that the summation of the weights is 1 and represents constant returns to scale (CRS).

Second, Tone (2003) constructed an SBM model with undesirable outputs, which can better calculate the relationship between input, output and pollution and solve the slack problem in the efficiency index. For $DMU_0(x_0,y^g_0,y^b_0)$:

$$\rho^*=\min\frac{1-\frac{1}{n}\sum_{i=1}^{n}\frac{S_i^-}{x_{i_0}}}{1+\frac{1}{u+v}\left(\sum_{j=1}^{u}\frac{S_j^g}{y^g_{j0}}+\sum_{j=1}^{v}\frac{S_j^b}{y^b_{j0}}\right)} \tag{A.2}$$

$$\text{s.t. } x_0=X\lambda+s^-$$

$$y^g_0=Y^g\lambda-s^g$$

$$y^b_0=Y^b\lambda+s^b$$

$$s^-\geq 0, s^g\geq 0, s^b\geq 0, \lambda\geq 0$$

where s^-, s^gands^b are the input slack, desirable outputs slack and undesirable output slack, respectively; ρ^* is the efficiency value of DMU (x_0,y^g_0,y^b_0) and strictly decreases; and $0\leq\rho^*\leq 1$. When $\rho^*=1(s^-=0,s^g=0,s^b=0)$, DMU is effective, while if $\rho^*<1$, at least one of s^-, s^gands^b is not equal to 0, and DMU is invalid. Therefore, the input-output model needs to be improved.

Third, the directional distance function in region a' at time t is introduced and is expressed as follows:

$$\overrightarrow{D_0}\left(x^t,y^t,b^t;g_v-g_b\right)=max\beta \tag{A.3}$$

$$\text{s.t. } \sum_{a=1}^{A}z_a^t y_{aj}^t\geq y_{a'j}^t+\beta g_{yj}^t, j=1,2,\ldots,u$$

$$\sum_{a=1}^{A}z_a^t b_{a's}^t\geq b_{as}^t-\beta g_{bs}^t, s=1,2,\ldots,v$$

$$\sum_{a=1}^{A}z_a^t x_{ai}^t\leq x_{a'i}^t, i=1,2,\ldots,n$$

where z_a^t is the weight value and a = 1, 2, …, A. Then, using the method proposed by Chung et al. (1997), the ML index of green TFP from time t to $t+1$ is finally obtained as below:

$$ML_t^{t+1}=\left[\frac{1+\overrightarrow{D_0}^t\left(x^t,y^t,b^t;g^t\right)}{1+\overrightarrow{D_0}^t\left(x^{t+1},y^{t+1},b^{t+1};g^{t+1}\right)}\times\frac{1+\overrightarrow{D_0}^{t+1}\left(x^t,y^t,b^t;g^t\right)}{1+\overrightarrow{D_0}^{t+1}\left(x^{t+1},y^{t+1},b^{t+1};g^{t+1}\right)}\right]^{\frac{1}{2}} \tag{A.4}$$

Because this paper's purpose is mainly to measure the contribution rate of green TFP to calculate the industrial green transformation, we do not decompose the ML index into an efficiency change and a technological progress source.

A.2. Distribution of Chinese provinces with different threshold intervals for each year.

Table S1
Distribution of provinces with different thresholds of environmental regulation

	REG≤11.764	11.764 < REG≤11.867	REG>11.867
2010	18	2	10
2011	17	2	11
2012	17	1	12
2013	17	2	11
2014	17	2	11
2015	17	2	11

Appendix B. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jclepro.2018.02.311.

References

Anderson, R.G., Chauvet, M., Jones, B., 2015. Nonlinear relationship between permanent and transitory components of monetary aggregates and the economy. Econom. Rev. 34 (1–2), 228–254.
Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev. Econ. Stud. 58 (2), 277–297.
Beijing Municipal Environmental Protection Bureau. Beijing Environmental Statement, 2014. Beijing Municipal Environmental Protection Bureau. China, Beijing, 2014.
Bin, L.I., Peng, X., Ouyang, M.K., 2013. Environmental Regulation,Green total factor productivity and the transformation of China's industrial development mode——analysis based on data of China's 36 industries. China Ind. Econ. 4, 56–68.
Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econom. 87 (1), 115–143.
Chang, D.-S., Kuo, L.-C.R., Chen, Y.-T., 2013. Industrial changes in corporate sustainability performance—an empirical overview using data envelopment analysis. J. Clean. Prod. 56, 147–155.
Chen, S., Yan, F., Wu, R., 2010. Capital deepening, productivity promotion and CO_2 emission in China. Fin. Trade Econ. 12, 111–119.
Cheng, Z., Li, L., Liu, J., 2017. The emissions reduction effect and technical progress effect of environmental regulation policy tools. J. Clean. Prod. 149, 191–205.
Cheng, Y.Q., Wang, Z., Zhang, S.Z., 2013. Spatial econometric analysis of carbon emission intensity and its driving factors from energy consumption in China. Acta Geograph. Sin. 68 (10), 1418–1431.
Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: a directional distance function approach. J. Environ. Manag. 51 (3), 229–240.
Diakoulaki, D., Mandaraka, M., 2007. Decomposition analysis for assessing the progress in decoupling industrial growth from CO 2 emissions in the EU manufacturing sector. Energy Econ. 29 (4), 636–664.
Dong, K., Sun, R., Hochman, G., Zeng, X., Li, H., Jiang, H., 2017. Impact of natural gas consumption on CO_2 emissions: panel data evidence from China's provinces. J. Clean. Prod. 162, 400–410.
Färe, R., Grosskopf Jr., S., Pasurka, C.A., 2007. Environmental production functions and environmental directional distance functions. Energy 32 (7), 1055–1066.
Hamamoto, M., 2006. Environmental regulation and the productivity of Japanese manufacturing industries. Resour. Energy Econ. 28 (4), 299–312.
Hansen, B.E., 1999. Threshold effects in non-dynamic panels: estimation, testing, and inference. J. Econom. 93 (2), 345–368.
Hou, J., Chen, H., Xu, J., 2017. External knowledge sourcing and Green innovation growth with environmental and energy regulations: evidence from manufacturing in China. Sustainability 9 (3), 342.
International Energy Agency (IEA), 2009. CO_2 Emissions from Fuel Combustion 2008 Edition. International Energy Agency (IEA), Head of Communication and Information Office.
Intergovernmental Panel on Climate Change (IPCC), 2007. Climate Change 2007: The Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, England, 2007.
Li, H., Shi, J.-f., 2014. Energy efficiency analysis on Chinese industrial sectors: an improved Super-SBM model with undesirable outputs. J. Clean. Prod. 65, 97–107.
Lin, B., Liu, K., 2016. How efficient is China's heavy Industry? A perspective of input–output analysis. Emerg. Market. Finance Trade 52 (11), 2546–2564.
Lin, B., Tan, R., 2017. Sustainable development of China's energy intensive industries: from the aspect of carbon dioxide emissions reduction. Renew. Sustain. Energy Rev. 77, 386–394.
Lin, B., Xie, X., 2016. CO_2 emissions of China's food industry: an input–output approach. J. Clean. Prod. 112, 1410–1421.
Lü, Y.-L., Geng, J., He, G.-Z., 2015. Industrial transformation and green production to reduce environmental emissions: taking cement industry as a case. Adv. Clim. Change Res. 6 (3), 202–209.
National Bureau of Statistics of China, 2015. China Statistical Yearbook on Environment. National Bureau of Statistics of China, Beijing, China, 2015.
Organization for Economic Co-operation and Development(OECD), 2002. Indicators to Measure Decoupling of Environmental Pressure from Economic Growth. Paris, 2002.
Porter, M.E., 1991. America's Green Strategy, pp. 193–246.
Schou, P., 2002. When environmental policy is superfluous: growth and polluting resources. Scand. J. Econ. 104 (4), 605–620.
Shanghai Academy of Social Sciences, 2014. Blue Book of World Cities: Annual Report on World Cities. Social Sciences academic Press(China), Beijing, China, 2014.
Shi, Q., Chen, J., Shen, L., 2017. Driving factors of the changes in the carbon emissions in the Chinese construction industry. J. Clean. Prod. 166, 615–627.
Sinn, H.W., 2008. Public policies against global warming: a supply side approach. Int. Tax Publ. Finance 15 (4), 360–394.
Sueyoshi, T., Goto, M., 2014. Investment strategy for sustainable society by development of regional economies and prevention of industrial pollution in Japanese manufacturing sectors. Energy Econ. 42, 299–312.
Suh, D.H., 2016. Interfuel substitution and biomass use in the US industrial sector: a differential approach. Energy 102, 24–30.
Tone, K., 2003. Dealing with Undesirable Outputs in Dea: A Slacks-Based Measure (Sbm) Approach. GRIPS Research Report Series 2003.
Wang, J., Zhao, T., Wang, Y., 2016. How to achieve the 2020 and 2030 emissions targets of China: evidence from high, mid and low energy-consumption industrial sub-sectors. Atmos. Environ. 145, 280–292.
Wang, K., Wei, Y.-M., 2014. China's regional industrial energy efficiency and carbon emissions abatement costs. Appl. Energy 130, 617–631.
Wang, L., Gong, Z., Gao, G., Wang, C., 2017. Can energy policies affect the cycle of carbon emissions? Case study on the energy consumption of industrial terminals in Shanghai, Jiangsu and Zhejiang. Ecol. Indicat. 83, 1–12.
Wang, Z., Yin, F., Zhang, Y., Zhang, X., 2012. An empirical research on the influencing factors of regional CO 2 emissions: evidence from Beijing city, China. Appl. Energy 100, 277–284.
Wanlley, W., 1994. The contribution of environmental regulations to slowdown in productivity growth. J. Environ. Manag. 8 (4), 381–390.
Xiaoli, Z., Rui, Y., Qian, M., 2014. China's total factor energy efficiency of provincial industrial sectors. Energy 65, 52–61.
Xie, R.H., Yuan, Y.J., Huang, J.J., 2017. Different types of environmental regulations and heterogeneous influence on "Green" productivity: evidence from China. Ecol. Econ. 132, 104–112.
Xu, B., Lin, B., 2016. Reducing carbon dioxide emissions in China's manufacturing industry: a dynamic vector autoregression approach. J. Clean. Prod. 131, 594–606.
Xu, B., Lin, B., 2017. Assessing CO 2 emissions in China's iron and steel industry: a nonparametric additive regression approach. Renew. Sustain. Energy Rev. 72, 325–337.
Xu, J., Yang, X., Tao, Z., 2015. A tripartite equilibrium for carbon emission allowance allocation in the power-supply industry. Energy Pol. 82, 62–80.
Yang, S., Bai, Y., Wang, S., Feng, N., 2013. Evaluating the transformation of China's industrial development mode during 2000–2009. Renew. Sustain. Energy Rev. 20 (C), 585–594.
Zhang, B., Xu, K., Chen, T., 2014. The influence of technical progress on carbon dioxide emission intensity. Resour. Sci. 36 (3), 567–576.
Zhang, X., Zhao, X., Jiang, Z., Shao, S., 2017. How to achieve the 2030 CO 2 emission-reduction targets for China's industrial sector: retrospective decomposition and prospective trajectories. Global Environ. Change 44, 83–97.
Zhao, M., Tan, L., Zhang, W., Ji, M., Liu, Y., Yu, L., 2010. Decomposing the influencing factors of industrial carbon emissions in Shanghai using the LMDI method. Energy 35 (6), 2505–2510.
Zhao, X., Zhang, X., Shao, S., 2016. Decoupling CO 2 emissions and industrial growth in China over 1993–2013: the role of investment. Energy Econ. 60, 275–292.
Zhu, J., Ruth, M., 2015. Relocation or reallocation: impacts of differentiated energy saving regulation on manufacturing industries in China. Ecol. Econ. 110, 119–133.